Lifelong Infinite Mixture Model Based on Knowledge-Driven Dirichlet Process

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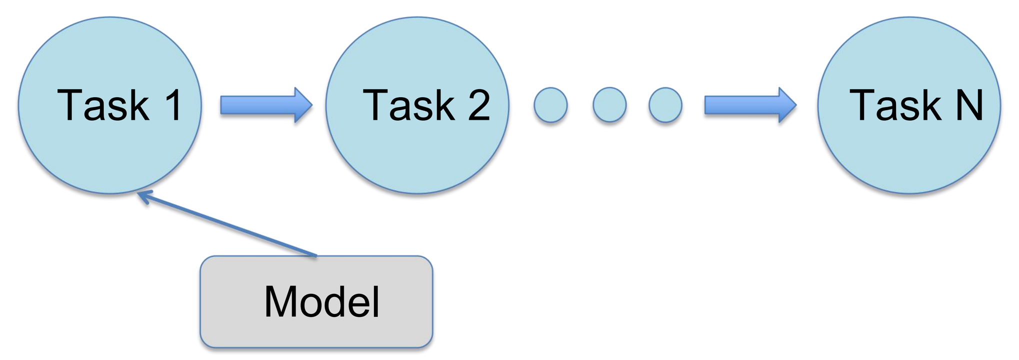
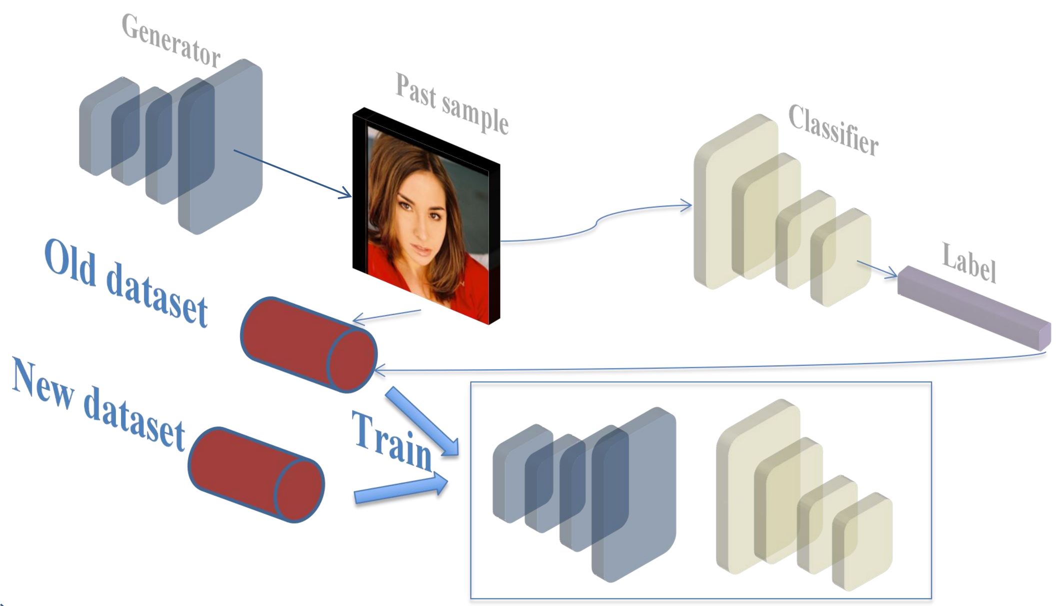
Introduction:

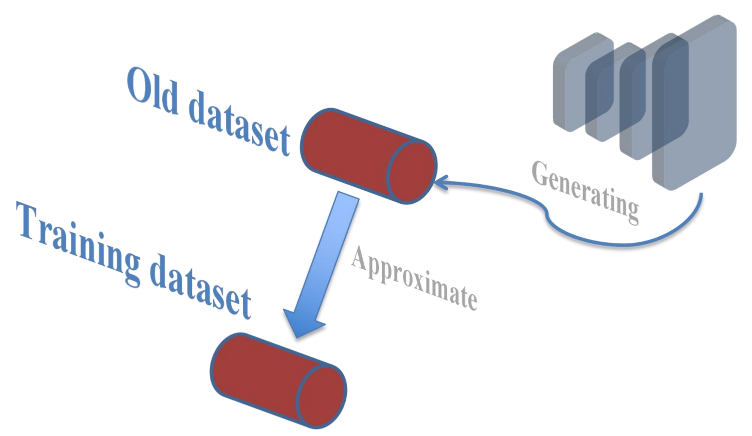


Lifelong learning (LLL) aims to learn successively a series of tasks from their corresponding probabilistic representations of specific databases.



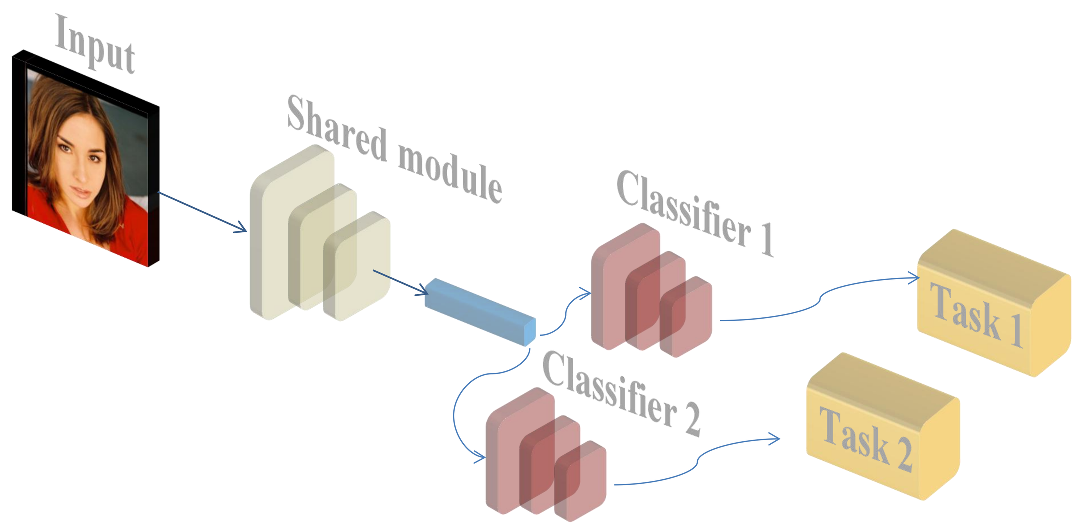
Generative replay mechanism (GRM) trains a generator as a generative replay network which is used to replay past data samples. The classifier and generator are trained on a joint of the past dataset and the new dataset.

The drawback of GRMn:



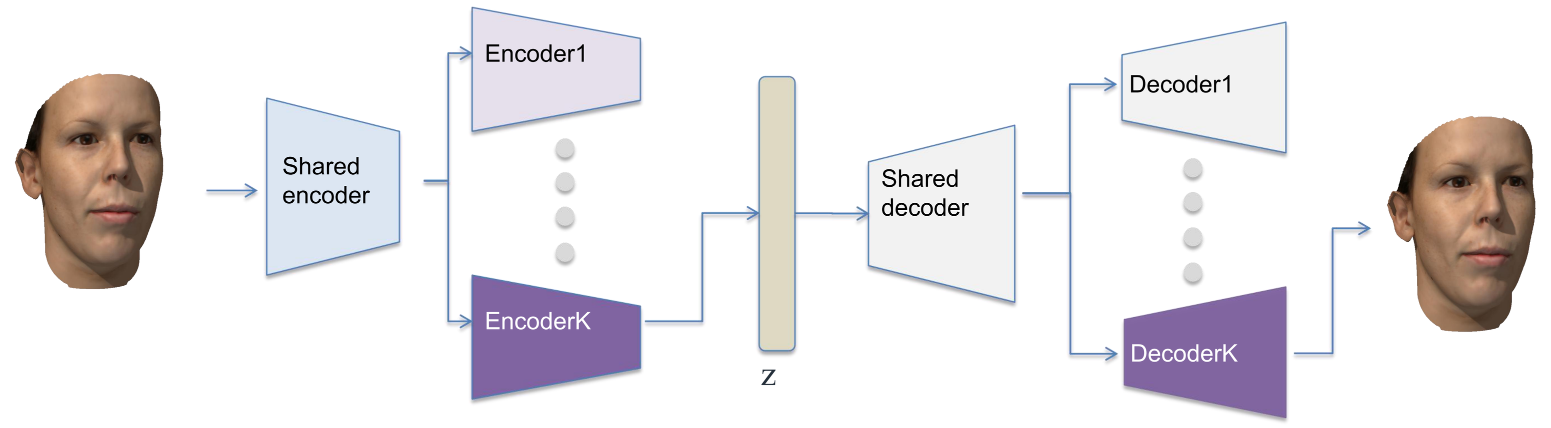
1. The old dataset can not approximate the corresponding training dataset exactly.

2. Generating a old dataset requires an extra memory.

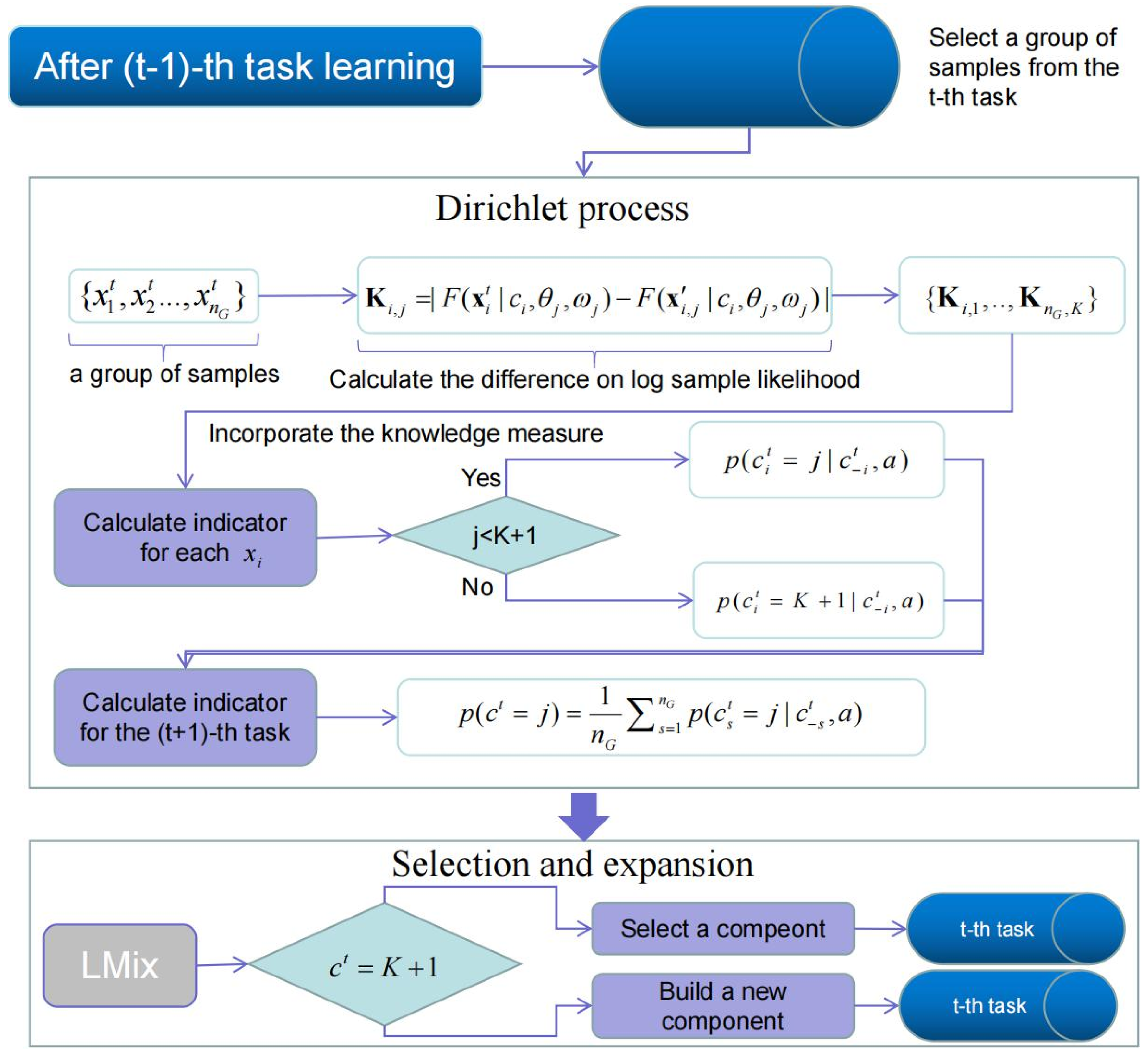


One solution is to expand the network architecture where the shared module is fixed after the first task learning.

Lifelong infinite mixture model (LIMix):



The network architecture of LIMix when training the K-th component at a certain task learning. Red colour representes the activated modules.



Step 1. We first collect a group of samples from the new task.
Step 2. We calculate the difference on log-likelihood of these collected samples.
Step 3. We calculate the expert index for each sample.
Step 4. We calculate the expert index for the new task.
Step 5. We perform the selection or expansion.

Experiment:

Dataset	LGM [32]	CURL [33]	BE[46]	LIMix	MRGANs [47]
MNIST	90.54	91.30	99.40	91.16	91.24
SVHN	22.56	62.05	74.46	82.60	64.12
Fashion	68.29	79.18	88.95	89.14	80.10
IFashion	73.70	82.51	86.45	88.70	82.19
RMNIST	90.52	98.56	99.10	98.80	98.30
CIFAR10	57.43	67.34	52.48	54.66	67.19
Average	67.17	80.16	83.47	**84.18**	80.52

We train various models under lifelong learning of MNIST, SVHN, Fashion, IFashion, RMNIST and CIFAR10.

Methods	Permuted MNIST	Split MNIST
DLP* [41]	82%	61.2%
EWC* [17]	84%	63.1%
SI* [50]	86%	98.9%
Improved VCL* [44]	$93.1 \pm 1\%$	$98.4 \pm 0.4\%$
FRCL-RND* [45]	$94.2 \pm 0.1\%$	$97.1 \pm 0.7\%$
FRCL-TR* [45]	$94.3 \pm 0.2\%$	$97.8 \pm 0.7\%$
FROMP* [29]	$94.9 \pm 0.1\%$	$99.0 \pm 0.1\%$
LIMix	**96.46**$\pm 0.03\%$ (10 C)	**99.21**$\pm 0.04\%$ (5 C)
LIMix	88.78% (7 C)	96.77% (4 C)
LIMix	95.25% (8 C)	91.37% (3 C)

We train various models under Permuted MNIST and Split MNIST.

Conclusion:

- We propose a new theoretical analysis framework for lifelong learning based on the discrepancy distance between the probabilistic measures of the knowledge generated by the model and the target distribution.
- Inspired by the analysis, we propose LIMix which performs better in cross-domain lifelong learning.